A Combined Approach for Lossless Image Compression Technique using Curvelet Transform

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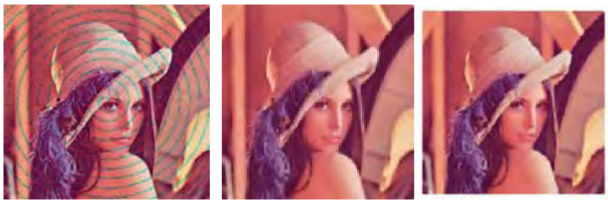
Abstract— **Image compression is an unavoidable research area which addresses the problem of reducing the amount of data required to represent a digital image for minimizing the memory requirement and system complexity. In the recent years, most of the efforts in the research of image compression focused on the development of lossy techniques. The key idea of our proposed scheme describes lossless compression using curvelet transform combined with error correcting BCH and modified arithmetic encoding technique. Most of the wavelet based approaches are well suited to point singularities have limitations with orientation selectivity and do not represent two dimensional singularities (e.g. smooth curves) effectively. Our proposed curvelet based approach exhibits good approximation properties for smooth 2D images. The BCH encoder converts the message of k bits in to a codeword of length n by adding three parity bits. The image can be divided into blocks of size 7 bits and entered to the BCH decoder which eliminates the parity bits. Thus the block of 7 bits will be reduced in to a block of size 4 bits and output will be in two folds. The first file contains the compressed image and the second contains the keys. The simulation results show that our proposed compression scheme gives more than 50% memory saving at peak signal to noise ratio (PSNR) 45 dB with 0.5 bit per pixel (BPP).**

Keyword- BCH coder, Bit per pixel, Curvelet transform, Image compression, Modified arithmetic coder, Peak signal to noise ratio.

I. INTRODUCTION

The primary objective of image compression is to reduce both spatial and spectral redundancy to store or transmit data in a proper manner and to reduce the number of bits as much as possible while keeping the resolution and the visual quality of the reconstructed image as close to the original image as possible. Lossy schemes provide much higher compression ratios than lossless but the reconstructed image is not identical to the original image. At the transmitting side, encoder performs three relatively straight forward operations such as transformation, quantization and coding. The goal of the transformation process is to pack as much information as possible into the smallest number of transform coefficients. Then the quantization stage quantizes the coefficients that carry the least information. The encoding process terminates by coding the quantized coefficients. In transform based image compression, it should de-correlate the spatially distributed energy into fewer data samples such that no information is lost and the inverse transform reconstructs the compressed image in the spatial domain. In transform based image compression, entropy coding minimizes the redundancy in the bit stream and is fully invertible at the decoding end. Discrete cosine transform (DCT) expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. It forms lossy compression of audio (MP3) and images (JPEG) where small high frequency components can be discarded. Modified discrete cosine transform is a Fourier related transform with the additional property of being lapped. It is performed on consecutive blocks of a larger data set where subsequent blocks are overlapped last half coincides with first half of next block. Among the existing codec, the most commonly used one is discrete wavelet transform (DWT) such as JPEG 2000 and SPIHT [1]. Over the past several years, the wavelet transform has gained widespread acceptance in image compression research. This avoids blocking artifacts at higher compression ratio but, the scale of wavelet decomposition cannot be fixed for the images with different content and produces poor compression ratio. Another compression technique which is called CALIC [2] have been developed for context formation, quantization, and modelling. It is more complex because of two modes of operations ie., binary and continuous tone modes and its compression performance also poor. The compression results of CALIC are shown in fig. 1 whose PSNR is 44.18 dB (MSE 4.11) with 2.13 BPP and compression ratio 3.345.



(a) (b) (c)

Fig. 1. (a) Damaged Image (192 KB) (b) Inpainted Image (184 KB) (c) Decompressed Image (192 KB)

The basic flaw of the above said compression method is its inability to represent edge discontinuities along curves and several number of coefficients are used to reconstruct edges properly along the curves. Therefore, there was a need of a transform that handle two dimensional singularities along the curves sparsely. This brought the introduction of new multi resolution curvelet transform. Curvelet transform [3] is a special member of the multiscale geometric transforms which will be superior over wavelets in following cases:

i) Optimally sparse representation of objects with edges.

ii) Optimal image reconstruction in severely ill posed problems.

iii) Optimally sparse representation of wave propagators.

Although curvelets is an extension of wavelets, there exist a correspondence between curvelet and wavelet subbands. The general rule that represents correspondence between curvelet subband (Cs) and wavelet subband (Ws) is

$$C_s \leftrightarrow W_s \,€ \left\{2 * C_s, 2 * C_s + 1\right\} \quad (1)$$

Fig. 2 indicates the Curvelet tiling [4] of phase and frequency plane. The left side of the figure represents the induced tiling of the frequency plane. The curvelets are supported near a "parabolic" wedge in Fourier space and the shaded area represents a generic wedge. The right side of the figure schematically represents the spatial Cartesian grid associated with a given scale and orientation.

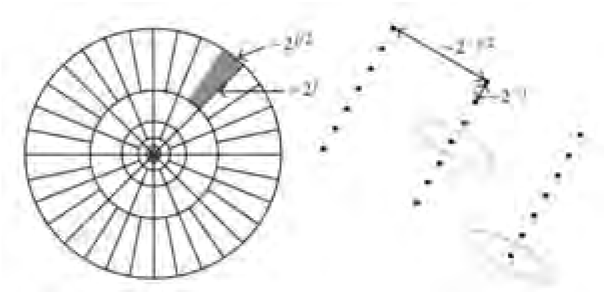


Fig. 2. Curvelet tiling of the frequency and phase plane

To construct a basic curvelet ϕ and provide a tiling of the 2-D frequency space, two ideas must be followed:

1. Consider polar coordinates in frequency domain

2. Construct curvelet elements being locally supported near wedges

Section II gives an idea about related work. Section III explains about proposed algorithm and Section IV discusses and evaluates the simulation results and finally Section V draws the conclusion.

II. LITERATURE REVIEW

The basic objective of image compression is the reduction of size for storage with good quality of reconstructed image and the number of researches have been carried out. Satish Kumar Singh et.al.[2] proposed novel adaptive color space transform and application by various contemporary standards by Joint Picture Expert Group which is been used for compression, exploited the correlation among the colour components using a component colour space transform prior to the sub band transform stage. Candes, et al.[3] discussed the digital implementations of two new mathematical transforms which are ridgelet transform and the curvelet transform. A central tool is Fourier-domain computation of an approximate digital Radon transform. They introduced a very simple interpolation in the Fourier space which takes cartesian samples and yields samples on a rectopolar grid which is a pseudo-polar sampling set based on concentric squares geometry. The curvelet reconstructions exhibit higher perceptual quality than wavelet based reconstructions, offering visually sharper images in particular higher quality recovery of edges. Jean-Luc Starck, et al. [4] had proposed a new method for contrast enhancement based on the curvelet transform which is well suited. Compared to wavelets, curvelet transform represents edges in a better way and is therefore well suited for multiscale edge enhancement. After the introduction of wavelets, it gave a different dimension to the compression. While handling the line and curve singularities in the image, some limitations are with wavelet. It also got affected by the blocking artifacts at high CR. But still there is a scope for higher compression with quality reconstruction. T. C. Lin, et al. [6] discussed an implementation of the discrete curvelet transform. The discrete curvelet functions are defined by a parameterized family of smooth windowed functions that satisfies two conditions ie., it should be periodic and partition of unity. Then, the transform is named as uniform discrete curvelet transform (UDCT) because the centers of the curvelet functions at each resolution are positioned on a uniform lattice. It has several advantages like less redundancy ratio, ease of implementation and hierarchical data structure . Ying Li, et al. [7] had proposed an adaptive method based on the mirror extended curvelet transform. Here, an improved gain function is introduced which integrates the speckle reduction with the feature enhancement to nonlinear shrink and stretch the curvelet coefficients which deals an important issue of suppressing the Pseudo-Gibbs artifacts. Andreas Klappenecker, et al. [9] addressed classical Bose Chaudhuri Hocquenghem (BCH) codes which can be used to construct quantum stabilizer codes. Furthermore, the dimension of narrow sense BCH codes with small design distance can be completely determined. Junho Cho, et al. [10] proposed a hardware efficient architecture for parallel implementation of the Chien search process in BCH decoders in which it transforms modulo multiplications into non modulo ones and converted to simple shift operations by changing the order of calculations. Since the number of finite field multiplications is much reduced, this method yields much better results when compared to previous optimizations based on lower complexities of finite field multipliers by redundant factor elimination. Elena Grigorescu, et al. [12] proposed explicit base for BCH codes which can admit very structured bases of small weight code words. H. S. Madhusudhana, et al. [13] presented deconvolution viewpoint for studying DFT domain decoding algorithms where some modifications is carried out to implement Blahut's decoding algorithm for 2-D BCH codes. Improved versions of Blahut's decoding algorithms were given for correction of random and burst errors. Navjot Kaur et al.[15] proposed multi layered image coding which combines curvelet and Haar transform to enhance PSNR and statistical parameters.AvishaKhanna et al.[16] presented curvelet-IWT based image compression to reduce memory for storage. This method gives better PSNR and CR.K.Siva Nagi Reddy et al.[17] proposed modified SPIHT based fast curvelet transform which dealt with curve functions in representing discontinuities along straight lines.L. Koteswara Rao et al.[18] discussed improved SPIHT based modified multiscale directional transform to enhance the visual quality and to increase encoding /decoding speed.

III.PROPOSED MODEL

In the pre processing stage, the image is denoised by two dimensional recursive filter and equalize the intensity of image using histogram equalisation. After forming curvelet coefficients, error correction is done by using BCH codes. Finally, encoded compressed image is obtained by using modified arithmetic encoding technique which is to be transmitted. At the decoder side, inverse process is carried out for reconstruction. The flow diagram of our proposed model is shown in Fig. 3.

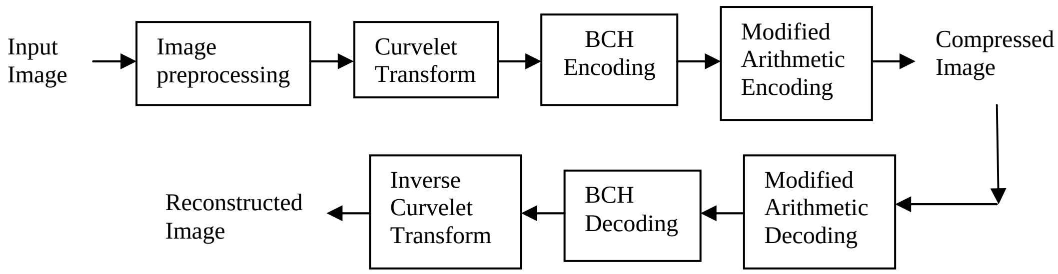


Fig. 3. Flow diagram of proposed model

A. Histogram Equalization

Histogram equalization is a process of producing uniform intensity image with the use of transformation function and the main advantage of histogram equalization is that the results are predictable.

In an image the probability of occurrence of gray level r_k is given by,

$$P_r(r_k) = n_k / n, k = 0,1,2,.....L-1 \quad (2)$$

Where n is total number of pixels in the image and n_k is number of pixels having gray level r_k.Enhanced image is produced by mapping each pixel with level r_k in the input image into a corresponding pixel with level s_k in the output image by using equation (3) is given by,

$$S_k = T(r_k) = \sum_{j=0}^{k} p_r(r_j) = \sum_{j=0}^{k} \frac{n_i}{n}, k = 0,1,2,...L-1 \quad (3)$$

The inverse transformation from s back to r is given by,

$$r_k = T^{-1}(s_k), k = 0,1,2,...L-1 \tag{4}$$

B. Algorithmic Approach for Curvelet Transform

A new multi-resolution transform was developed by Candes and Donoho in 1999 known as curvelet transform which removes the drawback associated with wavelet transform. Contrary to wavelets, isotropic principle[5] is used where length and width of support frame is of equal size in curvelet transform. Particularly, it was designed to represent edges and other singularities along curves much more efficiently than traditional transforms [6] and it uses many fewer coefficients for a given accuracy of reconstruction. It is clear to represent an edge, squared error 1/N requires 1/N wavelets but curvelet requires $1/\sqrt{N}$ [7].The steps involved in curvelet based image compression algorithm as follows.

Step 1: Read input image f.

Step 2: Apply the 2D FFT and obtain Fourier samples $\hat{f}[n1, n2]$, $-n/2 \leq n1$, $n2 < n/2$.

Step 3: For each scale/angle pair (j, l), resample (or interpolate) $\hat{f}[n1, n2]$ to obtain sampled values $\hat{f}[n1, n2 - n1 \tan \theta_l]$ for $(n1, n2) \in P_j$.

Step 4: Multiply the interpolated (or sheared) object $\hat{f}$ with the parabolic window $\tilde{U}_j$, effectively.

Step 5: Apply the inverse 2D FFT to each $\tilde{f}_{j,l}$, for collecting the discrete coefficients Cd (j, l, k).

The flowchart for the above said algorithm is shown in Fig. 4.

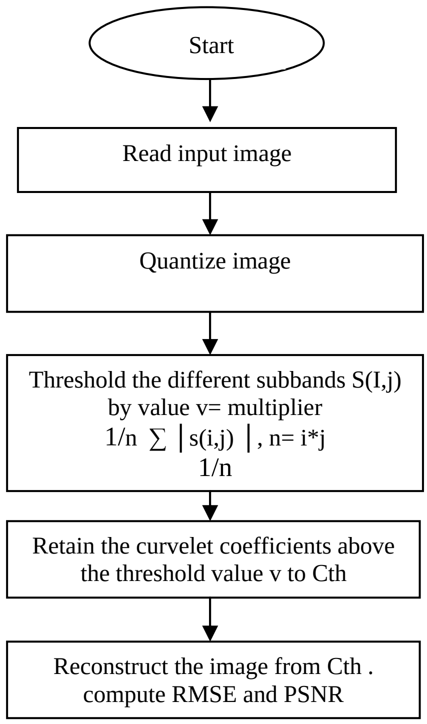


Fig. 4. Flow chart of curvelet transform

C. BCH Codes

The Bose, Chaudhuri, and Hocquenghem (BCH) codes [8]-[9] form a large class of powerful random error correcting cyclic codes. During code design, there is a precise control over the number of symbol errors correctable by the code and it is used to correct multiple bit errors. Another advantage of BCH codes is that ease of decoding named syndrome decoding [10] which simplifies the design of the decoder with low power electronic hardware. The binary input image is divided into blocks of size 7 bits each. Only 7 bits are needed to represent each byte, while eighth bit represents sign of the number (most significant bit) which does not affect the total value of blocks. Each block is decoded using BCH decoder [11], then it is checked whether it is a valid codeword or not. The BCH decoder converts the block to 4 bits. The proposed method add 1 as an indicator for the valid codeword to an extra file called map, otherwise add 0 to the same file. Once the image is compressed, the file (map) is compressed by run length encoding (RLE) to decrease its size and then it is attached to the header of the image. The BCH decoding process is repeated to improve the compression ratio [12]. If we continue this decoding process more number of times, it will affect the other performance factor such as compression time and map file size which leads to increase in size of image. The flowchart of BCH is shown in Fig. 5.

D. Modified Arithmetic Coding

The main aim of arithmetic coding is to assign an interval to each potential symbol and a decimal number is assigned to this interval. In modified arithmetic coding[13] ,a sequence of n symbols is represented by a number between 0 & 1 and no code tree needs to be transmitted which leads to achieve high compression ratio. After each read input, the interval is subdivided into a smaller interval in proportion to the probability of input symbols. The symbols of the alphabet are scaled into the new alphabet. In order to perform the interval reshaping, cumulative distributions are needed to keep upper and the lower bound values for the code intervals. Each rescaling will be based on the current symbol's range of cumulative probability. For a symbol $s_{k,}$ we have Symbol's Cumulative probability $C(s_k) = \sum^{k} i = 1P(s_i)$, probability of symbol s_i = $P(s_i)$.

The Low Bound for symbol

$$S_k = \sum^{k-1} i = 1P(s_i) = C(a_{k-1}) \qquad (5)$$

The High Bound for symbol

$$S_k = \sum^{k-1} i = 1P(s_i) = C(a_{k-1}) + P(s_k) = C(a_k) \qquad (6)$$

The low and high values are initially set to 0 and 1 respectively. Whenever a new symbol s_j is received, the low and the high values are updated as follows.

Range=high-low

Low=low + $\sum^{j-1}_{i=1} P(s_i)$ *(high-low)

= low + $C(a_{j-1})$*range

High=low + $\sum^{j}_{i=1} P(s_i)$ *(high-low)

= low + $C(a_j)$*range

This process runs recursively for all symbols in the input sequence and the final code lies between these high and low values. In the decoder, low and high values are initially set to 0. Let the received code be C. The range low becomes $C(a_{k-1})$ and high becomes $C(a_k)$. For all symbols

Low=low+$\sum^{k-1}_{i=1} P(s_i)$*(high-low)=low+$C(a_{k-1})$*range
High=low+$\sum^{k}_{i=1} P(s_i)$*(high-low) = low + $C(a_k)$*range

The next symbol k is such that

Low≤Low + $C(a_{k-1})$*range and Low+$C(a_k)$*range≤ High

Whenever a new symbol is observed, the transition frequency from the previous symbol to the current symbol is updated.

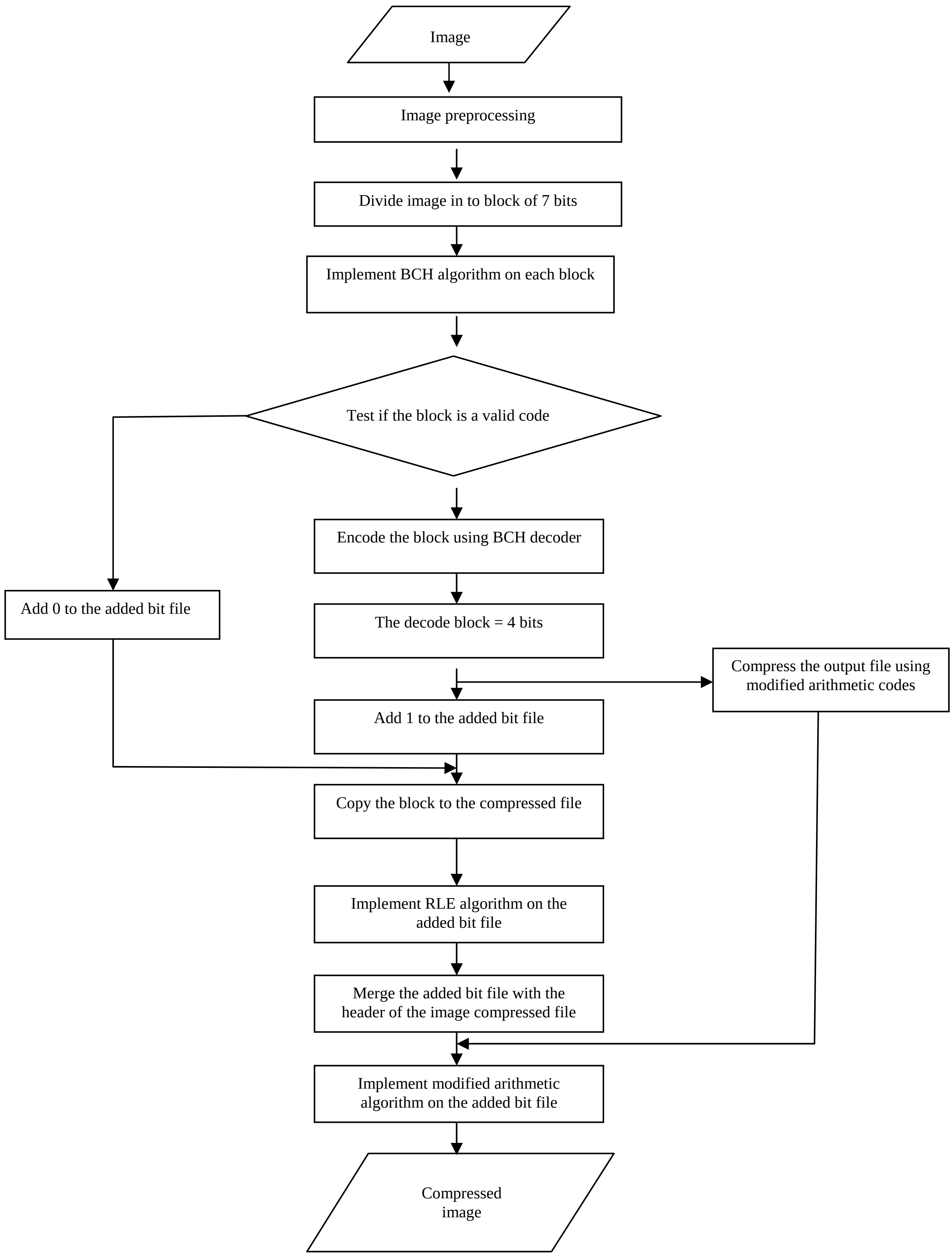


Fig.5 : Flow chart of BCH algorithm

IV. RESULTS AND DISCUSSIONS

In order to evaluate the effectiveness of our proposed compression algorithm, we have calculated primary metrics such as MSE, PSNR, CR ,BPP and it has been tested on different set of images with different size. The PSNR and Compression Ratio are calculated by using equations (7) & (8)

$$PSNR = 10\log_{10}\left[255^2 / MSE\right] \tag{7}$$

$$CR(\%) = Output\ file\ size(bytes)/Input\ file\ size(bytes) \tag{8}$$

Rate is an another important metric used to evaluate the performance of the compression algorithm which gives the number of bits per pixel (BPP) used to encode an image and is calculated as

$$Rate(BPP) = 8 * \left[size\ of\ image(bytes) / Pixel\ value\ of\ image(bytes) \right] \tag{9}$$

Simulation results are shown in Fig. 6 and its metrics with comparison results are tabulated in Table I & II with different input images. The results show that the proposed method has higher compression ratio, high PSNR and low BPP than other state of the art algorithm.

(a) (b) (c)

Fig. 6 (a) Original Image (b) Enhanced image using Fast Curvelet Transform (c) Reconstructed Image

TABLE I
Performance Index of Proposed Algorithm

Input Image		MSE	PSNR	CR	BPP
	Enhanced Image	0.1774	55.6403	35.3256	0.4667
	Image without Enhancement	17.2140	35.7720	35.3256	0.8866
	Enhanced image	0.2820	53.6276	32.3379	0.5670
	Image without Enhancement	17.4621	35.7098	32.3379	0.9030

TABLE II
Comparison Results with other State of Art Algorithm

Compression Scheme	**MSE**	**PSNR**	**CR**
DCT	11.47	19.28	7.957
MDCT	8.288	29.1965	9.231
QTD + DCT	9.4344	38.3837	12.975
QTD + DWT	7.355	39.553	13.242
This work	**0.1774**	**55.64**	**35.23**

V. CONCLUSION

The effectiveness of lossless image compression is enhanced by using curvelet transform combined with BCH and modified arithmetic coding which takes an advantage of BCH and modified arithmetic coding for the improvement of CR and BPP. This combined effect of BCH and modified arithmetic coding improves the quality of reconstructed image with considerable reduction of error pixels. Our method finds useful in several applications like satellite communication, wireless communication, CMOS image sensor etc. and it can be further enhanced for real time video compression with some necessary modifications.

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